MONITORING SPATIOTEMPORAL DYNAMICS OF HUMAN MOVEMENT BASED ON MAC ADDRESS DATA

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Keywords

Monitoring, Human Movement, Time Spending, Travel Time, Pedestrian, Cyclist, Walker, Runner, Bluetooth, Wi-Fi, MAC Address, Space Utilisation, Group and Individual Gathering, Scanner, Antenna Gain, Signal Strength, Environmental Interference

ABSTRACT

Monitoring human movement is an important topic in transport, crowd control, urban design and human behaviour assessment areas. Media Access Control (MAC) address data is used as the dataset for extracting movement features from people. MAC addresses are the unique identifiers for Wi-Fi and Bluetooth telecommunications in smart electronics devices such as mobile phones, laptops and tablets. The unique number of Wi-Fi and Bluetooth MAC address can be captured and stored by MAC address scanners. Due to the rapid increase of smart-phones and electronics devices, MAC address data can be used as a tracking technology. Increasing the popularity of cell-phones has motivated researchers to collect crowd data based on recording people's mobile phones. Monitoring vehicle movement in urban roads and motorways based on MAC data has been researched and applied in recent decade. Extracting new features from vehicles movement by MAC data was a motivation to use this data for monitoring people in public areas. MAC address data allows for unannounced, non-participatory, and simultaneous tracking of people. The use of MAC data for tracking people has been focused recently for applying in mass events, shopping centres, airports, train stations, etc.

However, limited research has been done in this area especially for indoor human monitoring purpose based on MAC address data. Also, a fundamental analysis of MAC address data for tracking human movement is essential in order to collect efficient and optimal data. The impact of scanning equipment and environmental obstacle on the range of MAC address dataset need to be evaluated. The empirical experiments were carried out to assess the impact of scanning equipment on the people movement monitoring.

The popularity use of Bluetooth and Wi-Fi devices has been compared in different environments. Wi-Fi popularity was highly more than Bluetooth popularity. This suggests that Wi-Fi MAC data must be focused more than Bluetooth in terms of human movement monitoring. Also, areas with free Wi-Fi networks motivated people to turn on their Wi-Fi devices.

The first case study has been done to measure pedestrians and cyclists' travel-time over a pathway using only one scanning point. Travellers were categorized based on their travel-time as pedestrians and cyclists. This set up offered less equipment cost, data size and complexity of processing.

In terms of applying MAC address tracking technology to monitor human movement in an indoor space, another case study was applied in the staff lounge

located in seventh floor of S block in QUT Gardens Point campus. This setting offers a challenging analysis in terms of human behaviour evaluation in office space utilisation including evaluation of lounge area utilisation frequency, daily time spending, daily utilisation peak periods, and group or solo utilisation. The goal of this case study was to explore the potential of MAC address tracking for studying the spatiotemporal dynamics of human in space utilization by highlighting a selection of analytical possibilities with the gathered data and showing the corresponding results. The main outcomes of this case study are listed below:

- Identifying the peak periods of daily utilisation,
- Identifying the peak weekdays of utilisation,
- Estimation of staff time spending is different time periods,
- Evaluation of group and individual attendance frequency and time spending.

This research showed that it is possible to analyse human behaviour in different aspects based on MAC address data, especially in terms of space utilisation. This dataset also can be a good source for researchers to study human's behaviour in terms of socialising and response to changes of environmental structure or design. Also, this information can be useful for evacuation planners to have better understanding of human behaviour in emergency conditions as well as contributing a significant improvement in crowd safety strategies.

CONTENTS

List of Figures

LIST OF TABLES

LIST OF ABBREVIATIONS

AP	Access Point
BSS	Basic Service Set
BMS	Bluetooth Media Access Control Scanner
CA	Collision Avoidance
DCF	Distributed Coordination Function
GIAC	General Inquiry Access Code
IEEE	Institute of Electrical and Electronics Engineering
LMP	Link Manager Protocol
MAC	Media Access Control
PCF	Point Coordination Function
TDD	Time Division Duplex
UWB	Ultra Wide Band
Wi-Fi	Wireless Fidelity
WPAN	Wireless Personal Area Network

Statement of Original Authorship

The work contained in this thesis has not been previously submitted to meet requirements for an award at this or any other higher education institution. To the best of my knowledge and belief, the thesis contains no material previously published or written by another person except where due reference is made.

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Date: 24/06/2014

CHAPTER 1: INTRODUCTION

Extraction features from spatiotemporal movement of human has become an interesting topic in terms of crowd congestion control, safety, public transport and human behaviour assessment. The robust passive and active positioning technologies have motivated the development of sensors which have the capability of human movement monitoring. Human movement behaviour analysis has received attention particularly in the field of visual analytics (Andrienko and Andrienko, 2007a, Andrienko et al., 2007). The demonstration and analysis of big volumes of trajectory data of objects moving through geographical space has recently become a major topic of interest in research areas such as computer science (Bogorny et al., 2009, Orlando et al., 2007), geographical information science (Ahlqvist et al., 2010, Shaw et al., 2008), urbanism (Van Schaick and Van der Spek, 2008), urban evacuation (Nassir et al., 2013, Nassir et al., 2014) and visual analytics(Andrienko and Andrienko, 2007b). The movements analysis of various kinds of objects including vehicles (Quiroga and Bullock, 1998), animals (Laube et al., 2007), bank notes (Brockmann et al., 2006) and typhoons (Terry and Feng, 2010) have been focused in recent studies. However, the greater part of research has been applied to people movement in different contexts and at various scales, the movement of athletes on a pitch (Laube et al., 2005), tourists on a regional (Ahas et al., 2008) and local scale (Kemperman et al., 2009, O'Connor et al., 2005, Shoval and Isaacson, 2007), and customers in a supermarket (Hui et al., 2009) for example.

1.1. RESEARCH PROBLEM

Surveys and video surveillance are the most common methods for customers and people data acquisition. However, high cost and also hardly representing of surveys because of a non-random sampling process are always a problem. Video processing is also depended on weather conditions, illumination changes, limited viewing angles, density and brightness of crowd (Liebig and Wagoum, 2012). Having difficulty to unambiguously distinguish between people in a crowd because of dense packing and constant interactions among individuals is another major shortcoming of video-based human data collection. The complexity of this method also increases with respect to the reconstruction of individual movements across multiple camera angles. Therefore, current applications of video data collection have achieved to capture the spatio-temporal paths of only limited objects in few spatial environments (Dee and Velastin, 2008), severely restricting its use as a tracking method in the context of human behaviour evaluation in space utilisation.

Increasing the popularity of cell phones has motivated researchers to collect crowd data based on recording people's mobile phones. Positioning the cell-phones based on Global System for Mobile (GSM) communication was proposed as a popular and accurate method but it has become less applicable most importantly due to the privacy objection (Giannotti and Pedreschi, 2008). In response to these issues and given the ubiquity of Bluetooth-enabled devices such as smart phones and tablets carried around by their owners, WiFi and Bluetooth technologies have increasingly been suggested as a simple and low-cost alternative for the reconstruction of spatial behaviour (Bullock et al., 2010a, Wasson et al., 2008, Versichele et al., 2010, Mottram, 2007, Van LonderseLe et al., 2009, Leitinger et al., 2010). Also, tracking individual in this method remains unknown avoiding potential privacy infringements because each fixed Media Access Control (MAC) address cannot be associated to any personal information such as names or mobile numbers. Bluetooth and Wi-Fi based monitoring data are also increasingly being used for road traffic monitoring and management (Tsubota et al., 2013a, Tsubota et al., 2014b, Khoei et al., 2013, Bhaskar et al., 2014c, Kieu et al., 2012b, Bhaskar et al., 2014a, Nantes et al., 2014, Kieu et al., 2014).

Monitoring people movement in urban and indoor spaces by capturing MAC addresses is new approach and has been introduced recently (Abedi et al., 2014). Most of works have been focused on only scanning and analysis of MAC addresses. Scanning equipment plays an essential role in data collection process. The impact of scanning equipment needs to be assessed in terms of optimal and efficient crowd data collection. Also, tracking human movement by capturing MAC addresses have been applied in different scenarios and environment such as festivals, mass events, stadium, urban path ways and train stations. Applying this tracking technology to monitor human movement in indoor spaces also needs to be tested. Because MAC address data allows for unannounced, non-participatory, and simultaneous tracking of people, it is especially useful to study the evaluation of human behaviour in terms of travel pattern, travel route choice, time spending and space utilisation.

However, limited research has been done in terms of monitoring human movement in indoor and outdoor spaces. Also, a fundamental analysis of MAC address data for tracking human movement is essential in order to collect efficient and optimal data.

1.3. RESEARCH AIMS AND OBJECTIVES

Addressing the aforementioned needs, this research actually goals to:

- Fundamentally understand the use of MAC address dataset for spatiotemporal monitoring of human movement in indoor spaces

This research indeed aims to significantly augment the current knowledge by reporting on a recent and comprehensive experiment using MAC address data as a tracking technology. Specifically, the objectives include:

- Evaluation of the features effecting on MAC address data collection process
- Applying MAC address monitoring technology to monitor spatiotemporal dynamics of human movement in terms of space utilisation

Real world experiments have been done to fundamentally analyse the effects of scanning equipments on data collection process in order to offer optimal setup in terms of human movement monitoring. The impact of antenna gain on the range of data collection is assessed. The popularity use of Bluetooth and Wi-Fi is evaluated in different environments in terms of crowd data acquisition. One case study was carried out at one of the staff office lounges of Queensland University of Technology in Brisbane, Australia in order to meet the second objective. This setting offers a challenging analysis in terms of human behaviour evaluation in shared space utilisation including evaluation of lounge area utilisation frequency, daily time spending, utilisation peak periods, and group or solo utilisation. The goal of this case study was to explore the potential of MAC address tracking for studying the spatio-temporal dynamics of human in space utilization by highlighting a selection of analytical possibilities with the gathered data and showing the corresponding results.

1.4. RESEARCH SCIENTIFIC AND PRACTICAL SIGNIFICANCE

The outcome of this research provides a fundamental assessment of using MAC address scanners for extracting features from human movement dynamics and behaviour. The real world experimental assessments of MAC address scanning equipment reveal essential information which effects on fundamental understanding of equipment and optimal MAC data collection. The outcomes of case study are expected to be used for studying human behaviour in response to space design, change and utilisation. The results of case study data analysis can be also used to significantly enhance the performance of facility management team in terms coordinating their staff, providing satisfactory quality service and facilities. It in fact results in balancing investment costs and quality service by optimal facility procurement and staff management.

1.5. RESEARCH LIMITATION

Some limitations were involved in this research. First of all, only one type of MAC address scanner was available for the experiments and data collection activities. The design of MAC address scanner's embedded system and firmware can be different depending on the manufacture. Also, antenna gain can be only variable in terms of scanner's hardware change. There was no control on the scanner's firmware to change scanning frequency and capacity.

1.6. THESIS OUTLINE

This thesis includes 5 chapters. Next chapter, Chapter 2, presents literature studied on human movement behaviour and MAC address data technology as a human monitoring tool. In Chapter 3, primary empirical experiments and results analysis for human monitoring based on MAC address data are presented. Then, Chapter 4 covers the main contribution of this study that is presented as case studies of extracting human movement dynamics based on MAC address dataset. Finally, Chapter 5 presents the conclusions and future research directions.

CHAPTER 2: LITERATURE REVIEW

2.1. OVERVIEW

This chapter presents literature reviewed around the research topic. Due to the focus on applying tracking human movement behaviour based on MAC address data, literature review chapter covers both human psychological movement behaviour and technical tracking methods. The first part of this section covers studies done on human behaviour in terms of movement. The second part presents technical literature related to employ MAC address as a tracking technology for extracting features from human movement.

2.2. HUMAN SPATIOTEMPORAL DYNAMICS OF MOVEMENT

Monitoring, simulation and predicting human's dynamics of movement patterns through space is becoming an increasingly important target of urban and transport planners interested in designing effective urban spaces for pedestrians (Batty, 1997, Batty, 2003). It is also an interesting area for studying and understanding human behaviour assessment in response to environment design and changes. However, such research and pattern extraction are not simple due to a large number of variables related to pedestrian, situations and environments. Some vide processing algorithms have been recently to count crowd (Ryan et al., 2009, Ryan et al., 2010) and extract their movement features.

The literature provides some insight relating to various elements of human movement behaviour in urban spaces. The most fundamental include walking speed and various distances people choose maintain between themselves and other entities around such as obstacle, building, kerbs etc. The walking speed of pedestrians in urban spaces varies between 1 and 1.5 meter per second (Polus et al., 1983, Virkler, 1998). Various factors may explain this walking speed variation. Personal factors such as gender and age significantly effects on walking speed (Boles, 1981, Knoblauch et al., 1996, Fugger et al., 2000). For instance, males walk faster than females and increasing age declines the speed (Bowman and Vecellio, 1994, Coffin and Morrall, 1995). Density of pedestrians also significantly effects on walking speed that it is demonstrated as speed-flow relationship (Fruin, 1992, Henderson, 1971). Other situational factors such as level of mobility and group size play a role (Boles, 1981, Knoblauch et al., 1996) as they are not received much attention in literature.

Environmental factor can also influence spontaneous walking speeds. Temperature affects people moving speed (Rotton et al., 1990). People moves more quickly when crossing roads (Lam et al., 1995). Overall function of pedestrian area such as shopping leisure, transport interchange, school route and business districts presumably varies pedestrian walking speed due to the differing priorities and targets of the people who populate them.

Studying the space preferences of pedestrians in urban and indoor spaces have essentially focused on establishing various levels of service criteria involving to pedestrian traffic in crowded or potentially crowded areas (Fruin, 1992, Pushkarev, 1975). Research suggested that people prefer to keep a buffer zone of approximately 0.45 meters between themselves and buildings' edges (Ciolek, 1978, Fruin, 1992), and a larger distance of around 0.85 between themselves and other pedestrians (Dabbs Jr and Stokes, 1975). Individuals also prefer to maintain the distance of around 0.1 meters from stationary items of street equipment (Habicht and Braaksma, 1984). One research also reported that people like to stay around 0.75 meters far from their companion(s) when walking (Burgess, 1983). However, most of these finding have remained actually uncorroborated (Kwon et al., 1998) as well as the influence of personal and environmental factors on these spacing behaviour. Nevertheless, these preliminary finding can be useful for designing of high-volume pedestrian facilities.

In terms of indoor and office environment movement, human movement can have different pattern compared to outdoor. Travel-time does not make sense in indoor and small scale spaces for example. Time spending and frequency of utilisation are the most significant of human behaviour in indoor and office environments. Cameras can be used as a tracking tool for extracting features from human movement in indoor spaces. However, because of lot of fit outs and panels, camera is an expensive way in this case. Bluetooth and WiFi addresses can be used as a tracking method which offer less equipment cost and process complexity. Surveys are also non random sampling and hard to represent. Rassia et al. studied human movement activities in office environments based on survey data. They found that the most of office activities are actually associated to personal initiatives which provide opportunities for informal interaction. Their outcomes indicate that people mostly move around desks, water cooler and printing desks (Rassia et al., 2009). Ramli et al. also tracked human movement in office spaces using video processing method. They developed an accurate model to track human movement activity by multiple cameras (Ramli et al., 2011). Watada et al. also proposed a prediction algorithm to forecast the direction of human movement using foot step direction (Watada and Musaand, 2008).

Understanding of human crowds during evacuations and panic conditions were researched since the 1930s (Kholshevnikov and Samoshin, 2008). However, there is limited understanding on the behaviour of panicking groups and its impacts on the safety under emergency situations (Helbing et al., 2000). The development of mathematical simulation models based on the collective movements of animals has been done since the 1970s (Okubo, 1986). In terms of studying human movement behaviour in the panic conditions such as emergency evacuations, some studies have been recently done to develop evacuation and crowd control models based on assessing animal dynamics. Shiwakoti et al. derived a mathematical model for crowd panic based on collective animal dynamics. They developed and validated their model by data experimented with panicking Argentine ants (Shiwakoti et al., 2011).

In terms of crowd congestion study, Hoogendoorn and Daamen also studied the microscopic behaviour in case of wide and narrow bottlenecks. Basically, pedestrian form layers or trails inside bottleneck. Their distance is measured approximately 45 cm which is less than effective width of a single pedestrian. This is called the phenomenon of “zipper” which corresponds overlapping of layers. Their finding shows that the phenomenon of “zipper” effect causes the capacity of the bottleneck to increase in a stepwise fashion with the width of the bottleneck. They found that two layers are formed in the narrow bottleneck (with of one meter), whereas four or five layers are formed for the wide bottlenecks (width of two meters) (Hoogendoorn and Daamen, 2005).

A well study of human movement behaviour and collecting efficient data from features impacting on human movement behaviour can lead to develop advance simulation platforms. Simulation models in fact offer a potential wealth to planners for predicting the movement of large number of pedestrian as they utilise various urban spaces (AlGadhi and Mahmassani, 1991, Blue and Adler, 1998). Such microscopic models can be differentiated based on rules and principles which underpin the movement decision of modelled pedestrians passing through virtual spaces (Gibson, 1978). In such models, pedestrians act based on evaluating the visual properties of pathways surfaces and making a movement decision according on which way offers them the best affordance (Hillier et al., 1993, Turner and Penn, 2002). Other models are mainly based on the principles that each pedestrian is motivated by a need to reach a particular target location by choosing the optimum path. This path may be determined by simple social force rules that explain people interactions with others in a range of crowded context (Helbing et al., 2001).

In terms of modelling pedestrian movement, PEDFLOW (Willis et al., 2000, Willis et al., 2002), for example, employs a context-mediated approach to select which movement decision is the most proper from a range of options linked with the prevailing situations (Kerridge et al., 2001, Kukla et al., 2001, Kukla et al., 2002). As another example, STREETS, an agent-based simulation model, look for route-choice behaviour at both microscopic and mesoscopic spatial scales by using a combination of deterministic route-finding and simple interaction rules (Haklay et al., 2001).

However, monitoring and simulating human movement is a complex procedure and requires information to understand various human movement characteristics related to physical, behavioural, emotional conditions. Data collection tools play an essential role to reveal these conditions and extract human movement patterns. Next section presents a new method for extracting pattern from human movement and behaviour.

2.3. MAC ADDRESS DATA AS A TRACKING TECHNOLOGY

2.3.1. Working Principle

In order to access networks and services with higher flexibility and mobility, wireless networks are a popular and fast-growing technology (Hossain and Wee-Seng, 2007). The benefits of wireless are reducing the cable restrictions, low cost, dynamic communication formation, and easy deployment. Bluetooth, WiFi, ZigBee, and UWB are four short range wireless standards that respectively correspond IEEE 802.15.1, 802.11 a/b/g, 802.15.4, and 802.15.3. In fact, IEEE defines the MAC address and Physical Layers for mentioned wireless protocols for an operation range of 10 to 100 meters. Bluetooth and ZigBee are most efficient in terms of power consumption and UWB and WiFi consume less normalized energy. Furthermore, ZigBee and Bluetooth have bigger transmission time and data coding efficiency associated to the data payload size (Porter et al., 2012). Nowadays, majority of smart-phones and digital devices use Bluetooth and WiFi technologies for communication.

MAC addresses are indeed unique identifies (see Figure 1) and are used for various type of communication networks and most of IEEE 802 network technologies. Hence, they can be tracked and this feature has been a motivation for various applications and data collection. Several factors may affect on the quality of MAC address data collection process that may be associated with the hardware and software implemented (Bhaskar and Chung, 2013).

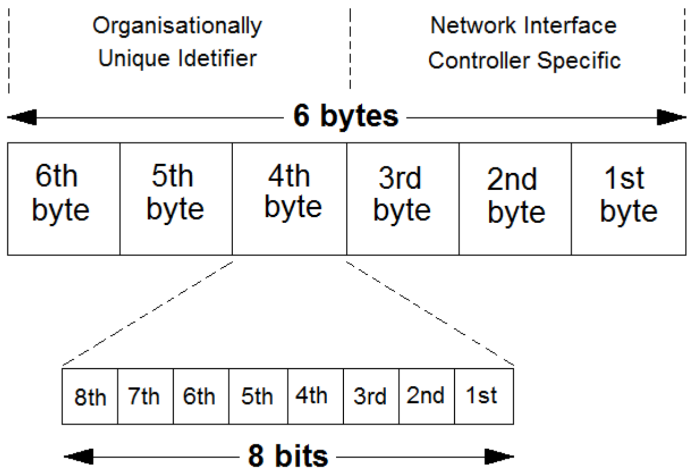


Figure 1. MAC address architecture. It includes 6 bytes that each byte consists of 8 bits. The first 3 bytes identifies organisation and other 3 bytes are the network interface controller specifics.

i. Bluetooth Architecture

Bluetooth known as *IEEE 802.15.1* is actually designed for short wireless range and mostly cheap devices in order to remove cables for peripheral computer data transmission such as mouse, printer, keyboard, and printer (Bray and Sturman, 2001). It is also very popular for short range transmission of data between electronic devices. *Piconet* and *Scatternet* are two connectivity topologies of Bluetooth technology. The *Piconet* is a Wireless Personal Area Network (WPAN) formed by the Bluetooth device and each *Piconet* is defined by a *Frequency Hopping Channel* based on the master's address (Porter et al., 2012). It is the Bluetooth network's building block that it is a small cluster of devices. *Piconets* indeed share a common physical channel and are synchronised to the same timeframe. They actually adopt the same Inquiry Hopping Sequence. Based on the *Piconet*'s structure, one device plays the master role and all other devices assume the role of slave. The slave devices then drive the sequence of channel-hopping according to the function of the master's clock and address. The Time Division Duplex (TDD) scheme is the transmission scheme adopted in the *Piconet*-based (Hossain and

Wee-Seng, 2007). A set of operational Bluetooth *Piconets* overlapping in a period of time is called Scatternet. Two *Piconets* can actually form a *Scatternet* (Porter et al., 2012).

Two main phases are required for the establishment of a Bluetooth-based connection (see Figure 2). Inquiry is the first phase and it in fact allows the inquirer to discover the possible slaves' identity. The second and final phase is named Page. This phase indeed corresponds to initial connection setup. In this phase the pager informs the paged unit regarding its identification status and defines its clock as the main clock. The Bluetooth devices are synchronised based on the inquirer/pager's (master) clock. The connection is then created and the devices begin the process of exchanging data (Bray and Sturman, 2001, Bisdikian, 2001, Hallberg et al., 2003, Hossain and Wee-Seng, 2007).

For Bluetooth MAC address based data collection, only the discovery section is needed and Bluetooth MAC address scanners never made a full connection with available Bluetooth device available. Inquiry and Inquiry Scan are the main parts of the Bluetooth device discovery protocol. The Inquiry part is run by a discovery device or Master and the Inquiry Scan part is run by a device willing to be discovered or slave. The Inquiry part includes Standby/Connection and Inquiry states. A device can be initially in Standby or Connection mode which is basically the *Link Manager Protocol* (*LMP*) layer. LMP layer in fact decides when the baseband layer my initiate the Inquiry part. When the device is in Inquiry state, two types of state transition occur that are *Tx* (transmission) and *Rx* (reception) slots. *Tx* and *Rx* frequencies of a discovering device are defined based on the Inquiry Hopping Sequence which contains the set of 32 distinct hope frequencies and is generated by discovering device's native clock and General Inquiry Access Code (GIAC). The set of 32 frequencies also is partitioned into two subsets of 16 frequencies. It takes 8 *Tx* slots for transmission of a whole subset of 16 frequencies and each time slot is 625 micro seconds. Because of the interleaved feature of *Tx* and Rx slots, the total duration for covering each subset of 16 frequencies is 16 slots or 10 ms (=16 x 625 micro seconds). Each subset is repeated 256 times before the other subset is used and 4 subsets must be used for collection of all responses in an errorfree manner. The Bluetooth discovery stage therefore lasts for 10.24 s (=256 x 4 x 10 ms) (Chakraborty et al., 2010). The Bluetooth discovery time is investigated empirically and presented in the Bluetooth and Wi-Fi comparison section.

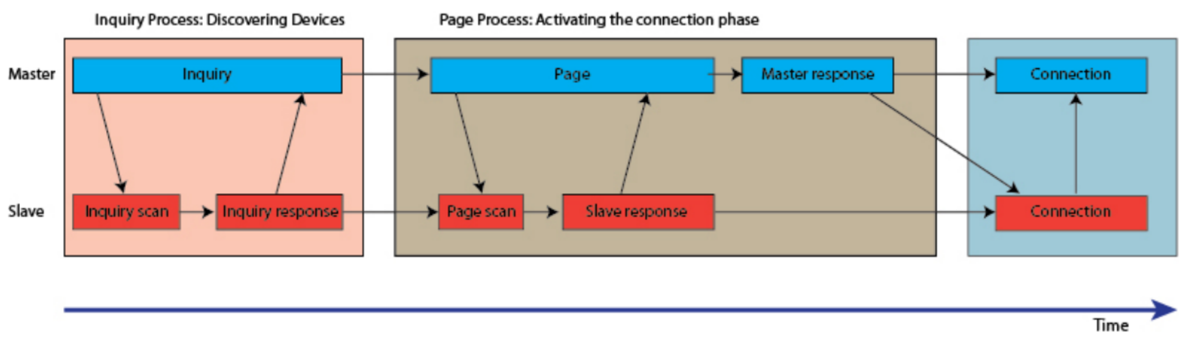


Figure 2. Bluetooth discovering and connection model (Bhaskar and Chung, 2013)

ii. Wi-Fi Architecture

Wireless Fidelity (Wi-Fi) also known *IEEE 802.11* (Gast, 2005, Crow et al., 1997, Ferro and Potorti, 2005, Willig, 2003) is designed for wireless local area network connections. Its purpose is to provide wireless connectivity for the devices such as cell-phones and PDAs which need quick installation. It defines MAC address for access to the physical layer. Users can surf the internet by Wi-Fi at broadband speeds through connection to an *Access Point* (*AP*) or ad hoc mode. Wi-Fi architecture includes several components which interact to provide a wireless connection. *Basic Service Set* (*BSS*) is the basic cell of a Wi-Fi network. *BSS* is a collection of mobile or fixed stations and a station cannot directly communicate with other stations of *BSS* if it moves out of its *BSS*. Coordination function is a set of rules which control the access to the transmission medium. Wi-Fi defies two main functions; *Distributed Coordination Function* (*DCF*) and *Point Coordination Function* (*PCF*). *Independent BSS* (*IBSS*) is the simplest Wi-Fi network. *DFC* is the fundamental of Wi-Fi MAC protocol that a *Carrier Sense Multiple Access with Collision Avoidance* (*CSMA/CA*) channel access technique (Porter et al., 2012, Harwood, 2009).

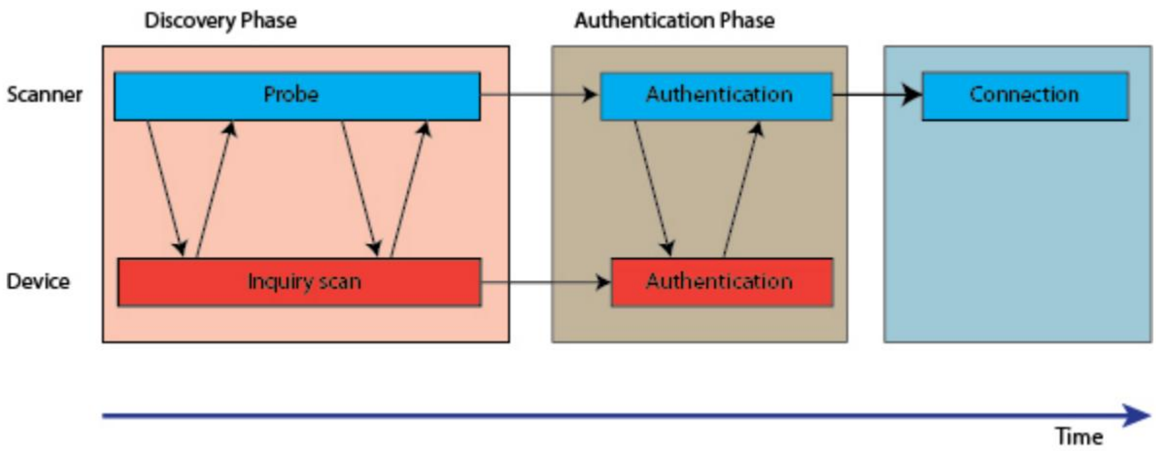


Figure 3. Wi-Fi discovery and connection model (Abbott-Jard et al., 2013)

Wi-Fi has two modes, *Active* and *Passive*, and uses *Scan*, *Authentication*, and *Association* procedures (see Figure 3). The scan procedure is applied for discovering MAC addresses and other Wi-Fi devices' parameters in the terminal's coverage area whether Wi-Fi is in the Active or Passive mode (Ferro and Potorti, 2005). Once a device has found an *AP*, it must operate *Authentication* with *AP* and then Association procedure. Since the *Association* phase has made with *AP*, the device can communicate with stations in other *BSS*s.

Same as Bluetooth MAC address scanners, Wi-Fi scanners also only operate the discovery section and never create a connection with around Wi-Fi devices. The discovery time for Wi-Fi is very less than Bluetooth discovery while both operate in a same radio frequency band. The reason is because of their difference in connection architecture. Han and Srinivasan pointed that discovering time of Wi-Fi addresses is dependant to the environment type. They noted that the Wi-Fi discovery time in a park, home and office is respectively measured 0.52, 0.87 and 1.07

seconds (Han and Srinivasan, 2012). The Wi-Fi discovery time is investigated empirically and presented in the next section.

Comparing Wi-Fi and Bluetooth technologies, both handle the traffic by a central unit called AP in Wi-Fi and Master in Bluetooth. The AP and Master are responsible for routing packets between devices. Bluetooth has maximum 7 slave units and Wi-Fi can support 2007 slaves. Also, the nominal range of Wi-Fi is 35 meters indoors and up to 100 meters outdoors and Bluetooth range is 10 meters for mobile devices. However, the range varies based on a function of transmission power and environment's complexity. Both Wi-Fi and Bluetooth need a global addressing procedure and a routing mechanism for ensuring stations global connectivity. A global addressing exists in Wi-Fi but Bluetooth does not provide any global addressing and it should be provided by the upper layer protocols such as the IP level (Ferro and Potorti, 2005). Due to switching the Bluetooth data signals based on the frequency hopping spread spectrum between radio frequency bands, they have a strong resistance to the environmental factors and interference. In direct sequence spread spectrum based communication of Wi-Fi technology, the system sends many redundant copies of data and a single copy is only needed for having full data transmission. It then can minimise the interference and background noise effects. It has also better signal delivery and security whereas it is a sensitive technology to many environmental conditions (Harwood, 2009).

Several factors may effect on the quality of MAC address data collection process that may be associated with the hardware and software implemented. Antenna characteristic is one of those factors. MAC address discovery time is also important in terms of collecting efficient data during a time period. Bluetooth discovery time is theatrically 10.21 seconds (Han and Srinivasan, 2012) whereas Wi-Fi discovery time is around 1 second (Chakraborty et al., 2010).

2.3.2. Related Works

Collection data from capturing wireless technologies such as Bluetooth and WiFi which communicate based on MAC address standards have been recently applied successfully. Nowadays, majority of smart phones, laptops, and portable electronics devices use wireless communication, especially Bluetooth and Wi-Fi. The presence of Bluetooth and WiFi networks in offices, buildings and campuses (Bisdikian, 2001, Bray and Sturman, 2001) have been increased because of their wide availability on a huge number of personal portable electronic devices. The use of Bluetooth Media Access Control Scanner (BMS) has been received significant interest from researchers and practitioners (Nantes et al., 2014, Bhaskar and Chung, 2013) in terms of complementary transport data. Time-synchronized BMSs installed on the road network has the potential to provide "live monitoring" of transportation of the Bluetooth enabled devices over the main roads. Assuming the devices are transported by the vehicles, individual vehicle travel time can be estimated. This approach is one of the most cost effective technologies of travel time on the main roads. In case of signalized urban arterials, where travel time estimation has always been very challenging with limited research (Bhaskar et al., 2009, Bhaskar et al., 2011, Bhaskar et al., 2013b, Bhaskar et al., 2013a, Bhaskar et al., 2014c, Khoei et al., 2013, Bhaskar et al., 2008, Bhaskar et al., 2010, Bhaskar, 2009, Tsubota et al., 2011), BMS provide a good estimation from individual vehicle travel time. Travel time from traditional matching of Bluetooth as ground truth travel time can be considered for validating other travel time estimation models (Tsubota et al., 2013b, Tsubota et al., 2014a, Bhaskar et al., 2014b) and forecasting future travel time values (Bajwa et al., 2005, Barceló et al., 2010). Bhaskar et al., (2014) have also developed algorithm to estimate trajectory of the Bluetooth equipped vehicles on motorways. These trajectories provide detailed statistics of travel time between any two points on the network between the BMS scanner locations (Bhaskar et al., 2014a). Other applications of BMS data in transportation include the assessment of work zone effects, traffic congestion analysis, route choice analysis (Xia et al., 2011), Origin-Destination analysis (Michau et al., 2014, Michau et al., 2013), travel time variability analysis (Kieu et al., 2012a, Kieu et al., 2012b). Bluetooth tracking technology has been applied for public transport utilisation in Graz (Weinzerl and Hagemann, 2007) and movement behaviour assessment in shopping centres (Millonig and Gartner, 2008).

With increasing the popularity of using mobile devices, new techniques have been presented for analysis of massive distributed movement data (Jankowski et al., 2010, Andrienko and Andrienko, 2007a). Tracking mobile phones and intercoms have been recently noticed as an effective crowd data collection and monitoring system (Liebig and Wagoum, 2012, Stange et al., 2011). Recent studies have been done on the analysis of people's travelling behaviour in the tourism industry (Jankowski et al., 2010) and pedestrian's density distribution during seasons (Andrienko et al., 2009).

Bluetooth technology has recently become an emerging technology for monitoring human dynamics of movement especially in airports, mass events, shopping malls etc. Some studies have been done on recording flows of outdoor movements using Bluetooth. Versichele et al., (Versichele et al., 2010) studied the potential and implication of Bluetooth proximity-based tracking in moving objects. Pels et al. implemented various scanners at Dutch train stations for capturing transit travellers (Pels et al., 2005). Weinzerl and Hagemann analysed the transit travellers and also tracked public busses by locating sensors inside the buses (Weinzerl and Hagemann, 2007). Versichele et al. used Bluetooth data as a tracking technology for analysis spatio-temporal movement of festival visitors (Versichele et al., 2012b). Versichele et al. also presented an intelligent event management with Bluetooth sensor network (Versichele et al., 2012a). Abedi et al. compared the popularity of WiFi and Bluetooth in terms of human movement data collection. Their study showed that WiFi is more popular and has higher scanning rate compared to Bluetooth devices (Abedi et al., 2013). Stange et al. also used Bluetooth tracking system for monitoring visitors with extracting their pathway choice (Stange et al., 2011). Delafontaine et al. Analysed spatio-temporal sequences in Bluetooth tracking data to examine the behaviour patterns of visitors at a major trade fair in Belgium (Delafontaine et al., 2012). Vu et al. presented a joint Bluetooth/WiFi scanning framework for assessment of the location popularity and people time spending in a university campus area (Vu et al., 2010).

2.3.3. Antenna Characteristics Impact

Antenna characteristic is one of those factors. Porter et al. categorised six different antennas for assessing their capability and suitability in the Bluetooth data collection process. They evaluated the antennas' performance for Bluetooth traffic data collection. Their study shows that vertically polarized antennas with gains from 9 to 12 dBi are suitable for a Bluetooth based traffic data collection. They also mentioned that the circular polarized antennas do not significantly improve the data collection process (Porter et al., 2012).

One of the primary stages in MAC address based data collection is to understand scanning equipment, especially antenna's type and detection range. Wi-Fi and Bluetooth antennas are basically two types, directional and omni-directional. Omni-directional antennas send and receive signals from any direction and directional antennas only cover one direction and limited angles.

Comparing to MAC address data collection for transport purposes, the role of antenna characteristics is more significant in crowd data collection field. For example, it is important to know that the antenna used for scanning MAC IDs is able to cover all area containing different types of environmental interference such as trees, tables, partitions and so on. Antenna can be designed in different power gains that highly impact on the antenna directivity and electromagnetic efficiency. The antenna power gain's unit is expressed in decibels and is called decibels-isotropic (dBi).

2.3.4. Environmental Complexity Impact

The interference of environment's obstacle on the wireless communication is a significant issue for setting a powerful and optimised wireless communication network. Some factors that cause considerable interference are (Harwood, 2009):

- Physical objects (such as Trees, masonry, buildings, and other physical structures),
- Radio Frequency (RF) interference (such as microwave and cordless phones),
- Electronics Device interference (computers, refrigerators, fans and lighting fixtures),
- Environmental factors (such as weather conditions, fog, and lighting).

While outdoor interference such as weather condition is not a serious problem, there are plenty of wireless obstacles in indoor spaces such as offices and homes. Table 1 presents the obstacle severity on wireless communication.

2.4. CONCLUSION

The first part of the literature review showed that people can have different speeds and movement behaviours in a similar environment and situation. Literature explained some common human movement behaviour such as walking speed and walking distance as well as studies done to model human movement behaviour. That part indicated that capturing new features from human's movement by commencing new technologies can increase human movement monitoring and simulation quality. Literature shows the potential of MAC address data as a cost efficient method for extracting human movement behaviour patterns. However, limited research has been done to access impacts of physical elements such as antenna characteristics on the MAC address dataset. As a result, a fundamental understanding of the MAC address data is required in order to increase monitoring accuracy and develop new applications. Also, the previous studies were focused on extracting features from people's movement based on only Bluetooth data at mass events or estimating people's waiting time and travel-time. However, Wi-Fi can be also used as a potential source for extracting people's movement patterns. In this research, monitoring human behaviour in case of space utilisation is studied to present a new application of MAC address data that presents the main contribution of this research.

Table 1. Obstacle severity on wireless signals (Harwood, 2009)

Obstruction	Obstacle Severity	Sample Use
Wood/wood panelling	Low	Inside a wall or hollow door
Drywall	Low	Inside walls
Furniture	Low	Couches or office partitions
Clear glass	Low	Windows
Tinted glass	Medium	Windows
People	Medium	High-volume traffic areas that have considerable pedestrian traffic
Ceramic tile	Medium	Walls
Concrete blocks	Medium/high	Outer wall construction
Mirrors	High	Mirror or reflective glass
Metals	High	Metal office partitions, doors, metal office furniture
Water	High	Aquariums, rain, fountains

CHAPTER 3: EMPIRICAL EXPERIMENTS

3.1. OVERVIEW

This chapter present the real-world experiments carried out to evaluate physical elements which impact on MAC address data collection process. The effect of antenna gain is assessed in order to fundamentally understand its impacts on the data collection. These assessments were the primary stages for the next experiments and the case study. Popularity of Wi-Fi and Bluetooth is also evaluated in terms of capturing likelihood.

3.2. EQUIPMENT

Figure 4 shows the hardware components used for data collection in this experiment. For capturing MAC addresses, a Wi-Fi/ Bluetooth scanner called CrossCompass (Acyclica, 2014) manufactured by Acyclica Inc with the capability of scanning Bluetooth and Wi-Fi addresses separately and simultaneously. This device can also be synchronised with GPS or PC clock. Based on experimental results, this scanner can scan Wi-Fi devices up to 15 meters and Bluetooth devices up to 10 meters without using any external antenna. It's Wi-Fi and Bluetooth discovery times are experimentally computed from over 10000 records. This device discovers Wi-Fi addresses every 1.365 seconds in average and Bluetooth IDs in almost 10.577 seconds. Because its minimum detection range and average discovery time are appropriate and suitable for the case study, this scanner was selected for data collection.

Figure 4. Wi-Fi and Bluetooth MAC address scanning hardware used for data collection: computational unit (1), Wi-Fi (2) and Bluetooth (3) antenna connector, USB storage (4), 3 dBi omni-directional antenna (5), LAN cable (6) for data connection to PC, 240v AC to 5v DC power convertor (6) and rechargeable 14v acid batter.

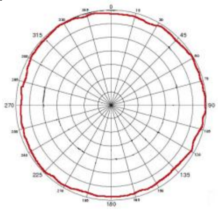
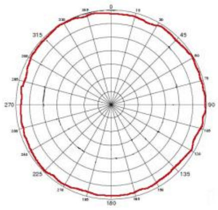
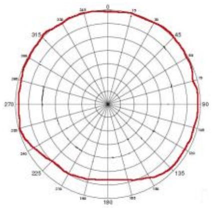
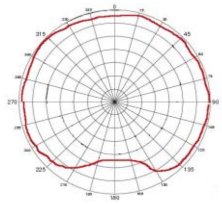
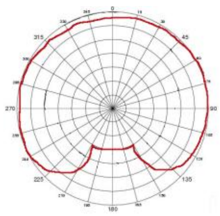
3.3. ANTENNA CHARACTERISTICS ASSESSMENT

As mentioned in the previous chapter, one of the primary stages in MAC address based data collection is to understand scanning equipment, especially antenna's type and detection range. Therefore, a detail assessment of antenna's detection range is required. The proposed scanning approaches in the following sections are dependent on how accurate the detection range of antennas is assessed. Figure 5 shows the equipment and experiment site location and Table 2 shows the experimental results for five different antenna's gains. The experimental results indicate that the Bluetooth discovery range in all gains is less than Wi-Fi detection range. Also, there is not a noticeable difference for discovery range in higher gains for both Bluetooth and Wi-Fi.

3.4. POPULARITY OF USE ASSESSMENT

Another issue that is important in MAC address-based crowd data collection is the popularity of using MAC addresses. In terms of assessing the popularity of using Wi-Fi and Bluetooth for crowd data collection purposes, a Wi-Fi and Bluetooth scanner with 5 dBi antenna gain were placed in six different locations categorized into:

Table 2. Antenna detection range for Bluetooth and Wi-Fi

Antenna Picture	Gain	Wi-Fi (Radius)	Bluetooth (Radius)	Horizontal Phase Plane
	2 dBi	70 m	45 m	
	3 dBi	90 m	75 m	
	5 dBi	140 m	100 m	
	7 dBi	150 m	110 m	
	10 dBi	150 m	120 m	

- Food court area
  - ***City food court*** *(no Wi-Fi provided) – Myer Centre food court, Brisbane, Australia, Between 11:30 AM and 1:30 PM on 6th of June 2013*
  - ***University campus food court*** *(Wi-Fi area) – Level 3 P Block, QUT GP campus, Brisbane, Australia, Between 11:30 AM and 1:30 PM on 4th of June 2013*
- Pedestrian pathway
  - ***Pedestrian pathway bridge*** *(no Wi-Fi provided) – Goodwill Bridge, Brisbane, Australia Between 10 AM and 12 PM on 7th of June 2013*

  - ***University campus pathway*** *(Wi-Fi area) – Queensland University of Technology (QUT) Gardens Point campus, Brisbane, Australia, Between 1 PM and 3 PM on 7th of June 2013*
- Office area
  - ***University staff lounge*** *(Wi-Fi provided) – Level 7 S block, QUT GP campus, Brisbane, Australia, Between 11:30 AM and 1:30 PM on 4th of June 2013*
- Entertainment facility area
  - ***Touch screen entertainment wall*** *(Wi-Fi provided) – Level 4 P Block, QUT GP campus, Brisbane, Australia, Between 11 AM and 1PM on 3rd of June 2013*

Figure 5. Experiment equipment and place (Kelvin Grove Oval, QUT KG campus)

For the two first mentioned categories, two places were selected for data collection, one place with no free Wi-Fi network and another with a free Wi-Fi network access. The purpose was to experimentally assess firstly the popularity of using Wi-Fi and Bluetooth devices in different places. Another aim was to evaluate if a free Wi-Fi coverage can effect on an increase in the observation rate of unique Wi-Fi addresses or not. Figure 6 shows the observation rate of unique Wi-Fi and Bluetooth MAC addresses in the mentioned places during peak periods for about two hours. In fact, the duplicated MAC addresses were removed and only unique IDs were considered. The results indicate that more than 90% of all scanned unique MAC addresses in all places were Wi-Fi addresses and the popularity of using Wi-Fi devices is therefore significantly more than Bluetooth ones. In another word, the likelihood of collecting efficient Wi-Fi devices is significantly more that Bluetooth. Also, the findings show that a free Wi-Fi network can effect on the observation rate of unique Wi-Fi IDs, however the effect is not noticeable.

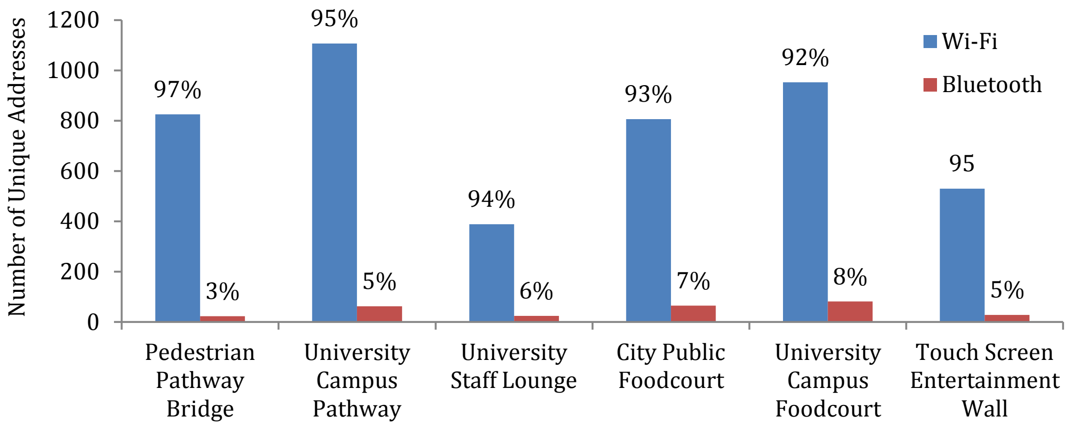


Figure 6. Experimentally assessment of Bluetooth and Wi-Fi popularity in different places

3.5. CONCLUSION

Antenna characteristics assessment experiments showed that higher gain antennas cover wider areas. However, there is no considerable difference in coverage for high gains. The results indicate that lower gain antennas are suitable for collection data from small spaces. Because pedestrian moves in small spaces, then understanding the exact range of scanning area is an important issue. Understanding the impacts of antenna gain is helpful to setup optimal antenna gain for pedestrian and cyclist travel-time estimation applications.

Evaluating the popularity use of Wi-Fi and Bluetooth devices in terms of crowd dataset showed that Wi-Fi has much more popularity than Bluetooth. Also, the areas providing free Wi-Fi increase the probability of observing more unique Wi-Fi MAC addresses. This suggests that Wi-Fi must be focused more than Bluetooth in terms human movement monitoring. The outcomes of these experiments suggested lower gain antennas for indoor and small areas in order to carry out the case study. Focusing on collecting Wi-Fi devices is also suggested to acquire efficient data for human indoor movement monitoring.

CHAPTER 4: CASE STUDY

4.1. PEDESTRIAN AND CYCLISTS

The previous methods for pedestrian travel estimation based on MAC address data have been done by at least 2 scanning points. The first contribution of this research is to estimate pedestrian travel time by only one scanning point. This method offers less data analysis complexity, process running time, equipment costs and resources compared to previous methods.

4.1.1. Experimental Design

In this case study, Bluetooth and Wi-Fi scanners were located almost in the middle of Goodwill Bridge (See Figure 7) between 10:30 AM and 12:30 PM on 7th of June 2013. 2dBi antenna gain was used for both Wi-Fi and Bluetooth scanners. The main reasons for choosing this pathway were:

- Only pedestrian and cyclists pass from this bridge
- People pass through this bridge with different movement speed

4.1.2. Pre-Processing

Along 2 hour data collection on Goodwill Bridge, 824 and 22 unique Wi-Fi and Bluetooth were scanned respectively. According to Table 3, the percentage of Wi-Fi unique IDs was much higher than Bluetooth ones. Figure 8 and 9 present the frequency observation number and percentage of unique MAC addresses. As the result, around 50% of Wi-Fi and 45% of Bluetooth addresses were scanned only once. Several issues may impact on once observation of a unique MAC address such as:

- High speed cycling and movement may cause only once record,
- MAC devices carried by City Cat and City Ferry (Brisbane river ferries) crows and passengers,
- People who turn off their devices when they are in detection zone,
- People who turn back after entering into the detection zone.

Figure 7. Data collection area map

The unique addresses that were observed once were not used for data analysis part because at least 2 records are required for travel time estimation. Due to the small sample of Bluetooth data, the rest of analysis in this section will be presented for Wi-Fi data. Figure 10 shows the number of unique Wi-Fi address every 15 minutes that 11:15 AM to 11:30 AM was the peak period.

Table 3. The number and percentage of total Wi-Fi and Bluetooth MAC addresses observed during 2 hour data collection

Unique IDs	Wi-Fi	Bluetooth
Number	824	22
Percentage	97.4%	2.6%

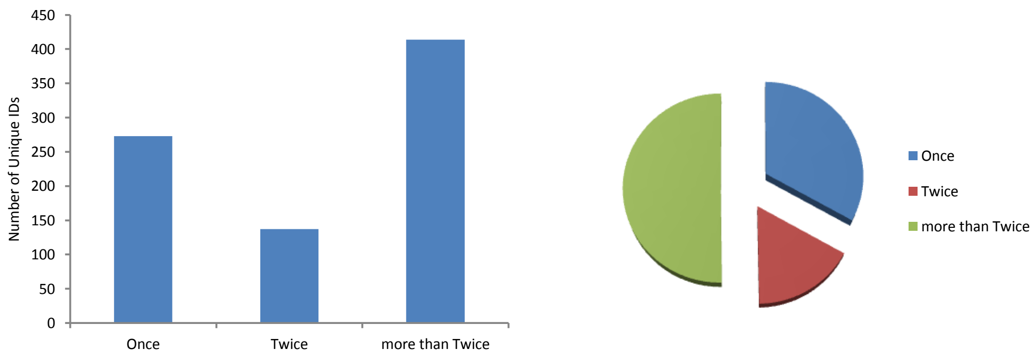


Figure 8. The number and percentage of observation frequency for unique Wi-Fi Addresses

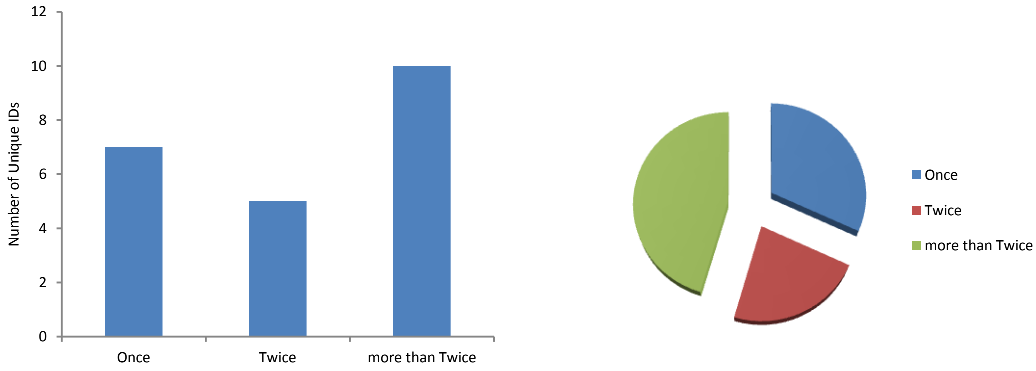


Figure 9. The number and percentage of observation frequency for unique Bluetooth Addresses

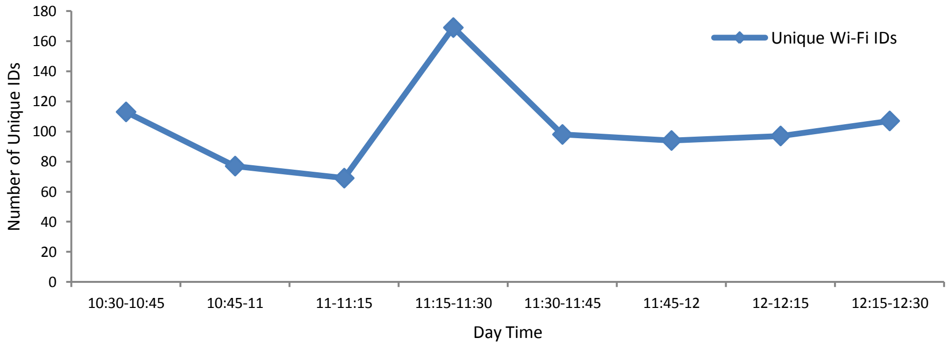


Figure 10. Number of unique Wi-Fi addresses observed in every 15 minutes

Previous research used at least 2 scanning points for pedestrian travel time estimation. In this research, the people travel time has been estimated by only one single scanning point. For this purpose, estimation of scanner's scanning range is the first step. During the data collection period, a mobile phone with active Wi-Fi and Bluetooth was from southern gate to northern gate of the bridge non-stop by a moderate pedestrian speed. A Bluetooth and WiFi mobile device were moved 395 meters during the experiment 5 times. Then the average speed of both devices can be calculated by dividing the travelled distance (395 m) into the average of all 5 travel-times (286, 283, 291, 294 and 281 sec) as follow

$$\overline{V} = \frac{dx}{dt} = \frac{395}{287} = 1.3763\, m/s$$

From Wi-Fi and Bluetooth scanners data, the duration between the first and last scans of all 5 test travel were as follow

$$Dt_{Wi-Fi} = 90,\ 99,\ 94,\ 96\ \ and\ \ 87\ \mathrm{sec}$$

$$Dt_{Bluetooth} = 49,\ 55,\ 56,\ 52\ \ and\ \ 48\ \mathrm{sec}$$

Then, the average travel-time for WiFi and Bluetooth devices were

$$\overline{Dt}_{Wi-Fi} = 93.2\,sec$$

$$\overline{Dt}_{Bluetooth} = 52\,sec$$

Now the average travel distance captured by each WiFi and Bluetooth scanner can be calculated as

$$\overline{Dx}_{Wi-Fi} = \overline{V} \times \overline{Dt}_{Wi-Fi} = 128.3\,m$$

$$\overline{Dx}_{Bluetooth} = \overline{V} \times \overline{Dt}_{Bluetooth} = 71.6\,m$$

Then, the scanning range for Wi-Fi and Bluetooth scanner can be estimated as

$$\overline{R}_{Wi-Fi} = \frac{\overline{Dx}}{2} = 64.15\,m$$

$$\overline{R}_{Bluetooth} = \frac{\overline{Dx}}{2} = 35.8m$$

Bluetooth scanner records MAC addresses at a scan cycle of 5 seconds. Due to which the error in observation can be 10 seconds. This will have significant impact on the range estimation. Then, the results only represent the effective scanning radius for this experiment. Figure 11 shows the scanning rage for Wi-Fi and Bluetooth on the data collection site. As can be seen from the picture, Wi-Fi scanner covers more area compared to Bluetooth scanner while both scanners use same antenna gain. The mobile device was moved from point A to point B by a moderate walking speed. Red circle is the area that the device's Wi-Fi was detected and Blue circle is the area that its Bluetooth was scanned. In the next section, the average speed of each MAC address will be calculated based on their travel time.

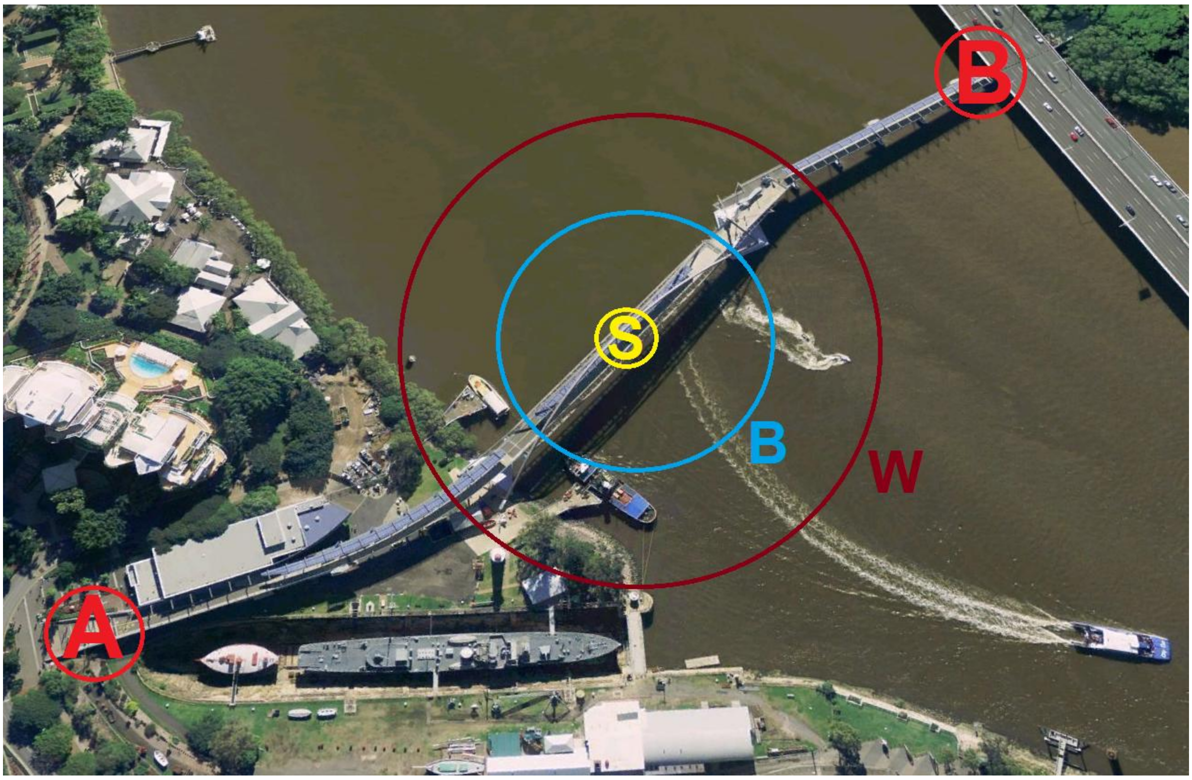


Figure 11. Wi-Fi and Bluetooth scanning range. S is the scanner's location, B is Bluetooth detection zone, W is Wi-Fi detection zone, A and B are the bridge's gates.

4.1.3. Results Analysis

In this section, the time period between the first observation and last observation of each MAC address has been calculated. From the previous section, the Wi-Fi and Bluetooth devices in the detection zone move 128.3 m and 71.6 m, respectively. Their average speed can be calculated by dividing their distance to travel time. Table 4 shows the distribution of Wi-Fi MAC addresses based on their travel time and average speed.

Table 4. Number and percentage of Wi-Fi MAC addresses distribution based on travel time and movement average speed. Blue and green columns correspond to the proportion of cyclists and pedestrian, respectively.

Time	**Less than 25 sec**	**25-60 sec**	**1-2 min**	**2-5 min**	**5-10 min**	**10-30 min**	**0.5-1 hr**	**Over 1 hr**
Speed (m/s)	**Over 5**	**5-2.14**	**2.14-1.07**	**1.07-0.43**	**0.43-0.21**	**0.21-0.07**	**0.07-0.04**	**Less than 0.04**
Number	104	58	48	36	39	61	38	76
Percentage	22%	14%	10%	8%	9%	13%	8%	16%

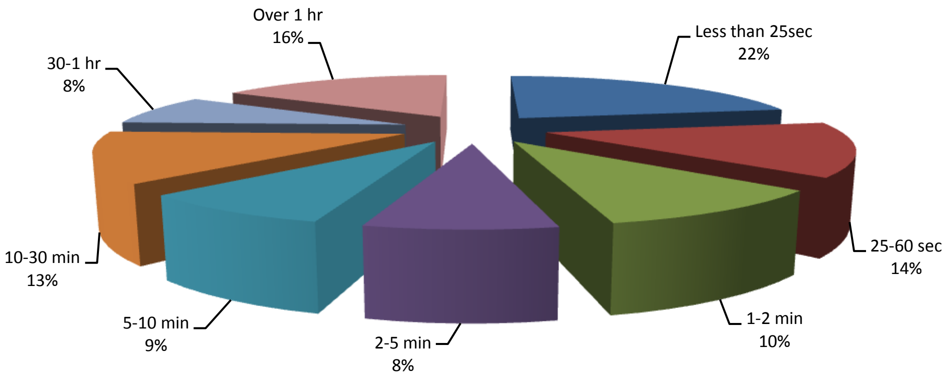


Figure 12. Time spent percentage distribution of Wi-Fi MAC addresses

According to Figure 12, 10% of unique IDs travelled the scanning area about 1 to 2 minutes. These 10% were counted as non-stop walkers. 14% travelled the area around 25 to 60 seconds which represents travel tome of a non-stop cyclists and runners. 22% of the unique samples can be categorised as noise because their travel-time is even less than a cyclist. The remaining 52% of MAC IDs cannot be categorises as a cyclists, runner or walker because their travel time does not match to an active cyclist, runner or walker. This proportion of IDs can be people who stopped in the middle of the bridge in order to visit the bridge's view or taking rest.

The experiment had been done in a sunny weather. However, a heavy rain or fog can impact on the detection range of scanners. Detection zones must be big enough to detect all objects moving by different speeds. Walkers move slower than runners and cyclists. Therefore, scanners can capture more samples from a walker compared to a cyclist because faster people spend less time in detection zones during their journey.

Compared to the multi-point scanning method, this method has lower cost and less computation running time and complexity. However, the direction of people cannot be identified by this approach. Also, this method can only categorise people who pass the area non-stop. Unlike monitoring people movement based on positioning technologies through GSM, GPS and GPRS, it is not possible to detect the instantaneous speed of people by MAC address samples. Also, the MAC devices which spent time more than a walker's travel time can be categorized as the people who had few stops during their journey. However, we cannot certainly categorise other 54% as people who stopped during their travel because data collection period was not big (2 hours). Larger dataset in terms of recording time will give more confidence in order to categorise people into more groups.

4.2. SPACE UTILISATION EVALUATION

4.2.1. Overview

The second case study presents the main contribution of this research. Human behaviour in terms of shared space utilisation is monitored based on analysis of MAC address data. This case study was applied in a staff lounge of an office environment. This setting offers a challenging analysis in terms of human behaviour evaluation in office space utilisation including evaluation of lounge area utilisation frequency, daily time spending, daily utilisation peak periods, and group or solo utilisation. The goal of this case study is to explore the potential of MAC address tracking for studying the spatiotemporal dynamics of human in space utilization by highlighting a selection of analytical possibilities with the gathered data and showing the corresponding results.

4.2.2. Experimental Design

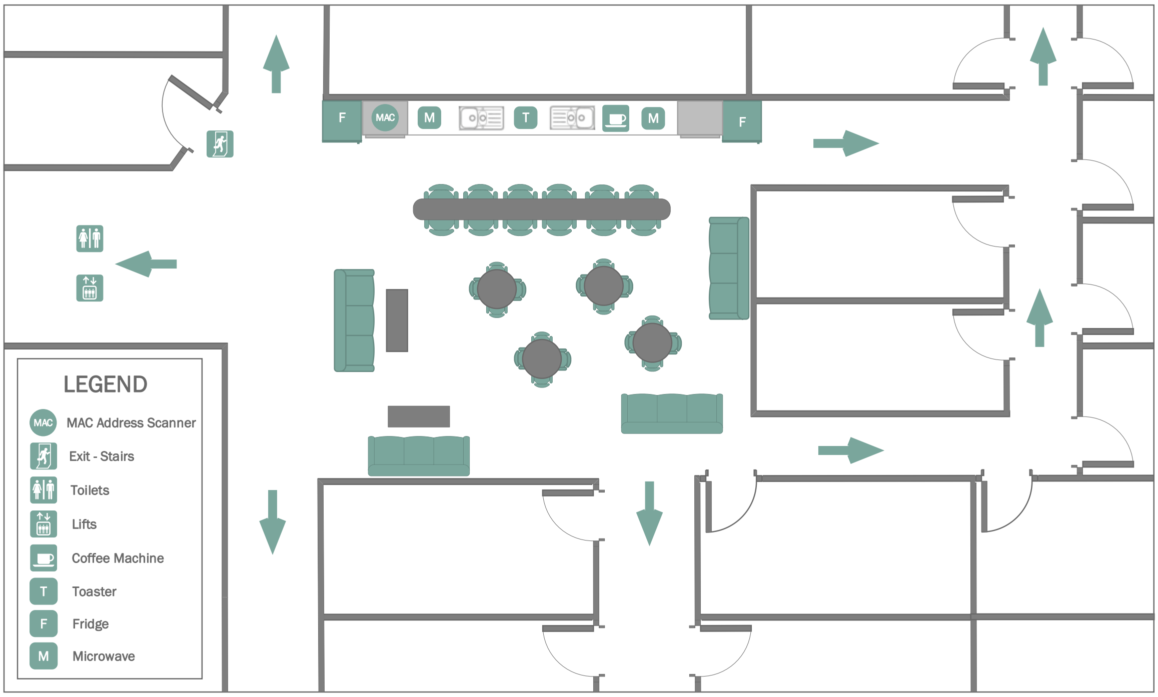
The area proposed for case study is one of the staff lounges of Queensland University of Technology (QUT) in Brisbane, Australia. It is actually located in the seventh floor of S block in QUT Gardens Point campus. Around 50 people including university lectures, academic research fellows and research students are allocated to this floor. Also, there is not any lecture room in this floor and it is only allocated to research students and staff. Other research staff from level 6 and 8 may come to this floor as it is fashion designed and widely equipped. As can be seen from Figure 13*a*, this area includes kitchen, dining tables and resting sofas. The MAC address scanner was located into one of kitchen cabinets shown by “MAC” sign in the spatial map in Figure 13*b*.

This area was selected for experimental implementation because various groups of research and academic staff utilise this area for dining and spend their leisure times. Also, group gathering for dining or drinking has been observed many times in this space. As a result, it was proposed as a place that socializing behaviour profile of human can be also detected, tracked and analysed. Except staff, other people including undergraduate student and ordinary people as a visitor may come to this area. In addition, this space provides free wireless network for QUT staff and students that increase the likelihood of capturing more WiFi devices.

4.2.3. Pre-Processing

The raw data consisted of log files on the implemented scanner has the following format: timestamp of detection, MAC address of the detected devices and signal strength. Figure 14 shows an extract of logged data. After merging the log files of three weeks, the dataset consisted of 35,873 loglines and 418 unique devices. In order to obtain a compressed dataset, unique addresses which were scanned only once daily or observed once a week have been removed. Also, the MAC addresses that their interval between the first and last observations was less than 4 minutes during a period of 1 hour have been considered as passing visitors and filtered. Different scenarios such as picking and dropping food in the fridge were done in order to estimate minimum time period that can be counted as utilisation period. Results of these experiments showed that over 3 minutes must be considered for area utilisation period. Furth-

(a)



(b)

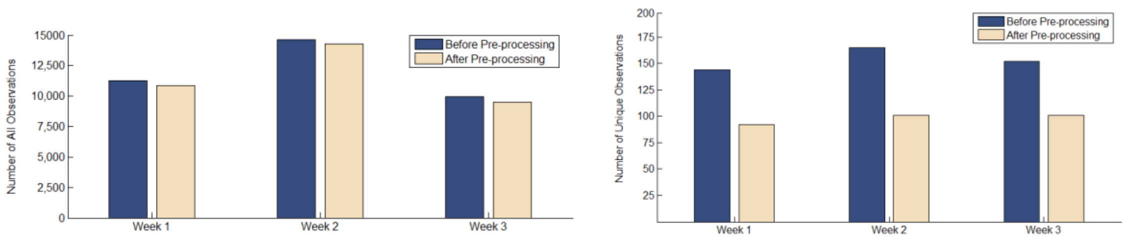
Figure 13. a) Picture and b) spatial map of the case study environment

ermore, all records over night periods were not considered as useful data for analysis. The devices which were scanned for long hours or entire business hours were counted as noise and removed. In this way, the dataset was compressed to 34,622 loglines and 239 unique devices.

1373033902	38:e7:d8:02:9c:c7	-76
1373033904	38:e7:d8:02:9c:c7	-76
1373033904	f8:db:7f:7c:5c:3e	-75
1373033906	f8:db:7f:7c:5c:3e	-74
1373033906	3c:5a:37:0a:20:4f	-77
1373033909	3c:5a:37:0a:20:4f	-71

Figure 14. Extract of logged data demonstrating the raw time detection data on Friday 5th July 2013 between 14:18:22 to 14:18:29. The first column represents date and time in UTC format. A Wi-Fi MAC address (f8:db:7f:7c:5c:3e), for example, being detected twice from 14:18:24 (1373033904) and 14:18:26 (1373033906) on Friday 5th July 2013. The third column indicates detected signal strength.

Figure 15 shows the distribution of collected data before and after pre-processing stage. Figure 15*a* has distribution from all the observations, whereas Figure 15*b* is from the unique records. The graphs indicate that there is not a significant drop in the number of records (*see* Figure 15*a*) while the number of unique devices was compressed to almost 30% (see Figure 15*b*). The pre-processing stage thus filtered ineffectual records and unique IDs. Figure 16 illustrates the distribution of detected unique Wi-Fi address during for three consecutive weeks over time after pre-processing. Here the unique records for each time period are cumulated for the three weeks. Lower, middle and upper band in Figure 16 represents records for Week 1, Week 2 and Week 3, respectively. As expected, the highest proportions of unique observations are from 10 AM to 6 PM during all three weeks.



(a) (b)

Figure 15. Distribution of data before and after pre-processing stage

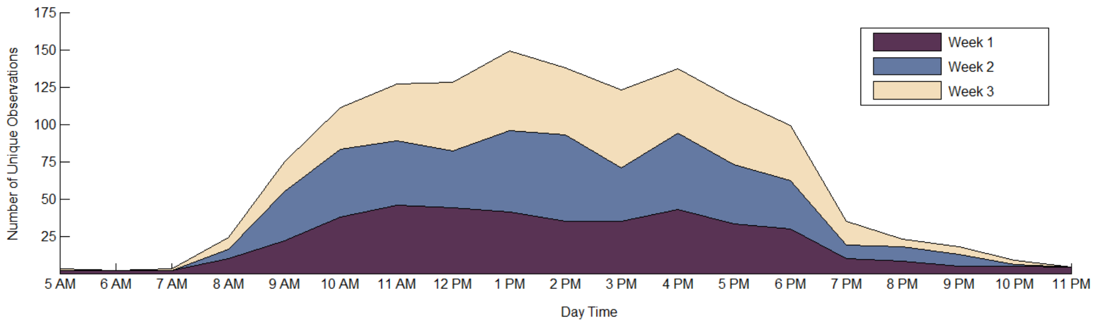


Figure 16. Distribution of the detected Wi-Fi address during for three consecutive weeks over time after pre-processing phase

4.2.4. Results Analysis

i. Frequency of Utilisation

This section presents the behaviour of staff in terms of utilising the lounge area during all three weeks. Figure 17 illustrated the radar plot for common devices for each week where the number of unique records of a particular week day and the number of these records observed in other week days are presented. For instance, red line with square represents unique records observed on Tuesday. Here for Week-1 (first plot in Figure 17) we have observed 40 unique MAC records on Tuesday. Out of this 40 unique ID we have observed 10, 10, 15 and 10 records on Monday, Wednesday, Thursday and Friday, respectively. From Figure 17 it can be concluded that between 8 to 10 staff utilise the area on all week days in each week, because there is no observation less than 8. The pattern of all three weeks is similar, with peak on Thursdays. This indicates that people who mostly use the area repeat similar weekly habits in terms of space utilisation.

The distribution of staff attendance of the area along each week is presented in Figure 18. Here, blue bar, light brown, and dark brown represents percentage of regular visitors for all the 5 days, 4 days and less than 3 days, respectively. It is observed that the over 50% of visitors utilise the area for 4 business days a week. Only 10% -15% of visitors are regular users for all the 5 days.

Figure 19 focuses on the distribution of common unique devices captured within different time period of the day and for different days of the weeks. Here each radar plot is for a specific day of the week. It is observed that:

a) Tuesday, Wednesday and Thursday have three peaks at 9:00-11:30 AM; 11:30 AM-2:30 PM; 2:30-5:30 PM, indicating the time when most of the people utilising the area.

b) Monday has only two peaks during 11:30 AM-2:30 PM and 2:30-5:30 PM and. This indicates that most of the people come to the area during lunch (11:30-2:30 PM) and afternoon tea (2:30-5:30 pm) but not much during morning (9:00-11:30 AM).

c) Friday, the distribution is scattered and its pattern is different from other days of the weeks.

This indicates that the utilisation of the space over different time of the day and day of the week is different with Monday and Friday having different patterns than the other working days. Though, majority of detected staff utilised the shared area during lunch period (11:30-2:30 PM) for all the working days.

Figure 20 demonstrates the proportion of staff utilisation frequency over three weeks. Here X-axis (*number of visits*) is the number of time periods a person is observed during the week and Y-axis is the percentage of such observations. The day is divided into 5 time periods (*Early Morning* (6:30 to 9), *Morning* (9 to 11:30), *Lunch Time* (11:30 to 14:30), *Afternoon* (14:30 to 17:30) and *Dinner Time* (17:30 to 20), *Refer to* Figure 19). Let's take an example to explain the graph. Say, a person is observed during two time periods (11:30 AM-2:30 PM and 5:30 PM-8:00PM) on Friday in Week-1 then this observation will be considered as *twice* visits in Week-1. If the same person is observed on another day for only a time period then this observation will also be considered as *once* visit in the respective week. Analysing the graph in Figure 20 we can conclude that: a) The majority of the staff utilised the area *twice* a day in all three weeks; and b) Less than 3% used the lounge only one period per day. Hence the lounge is utilised by a person for multiple times a day.

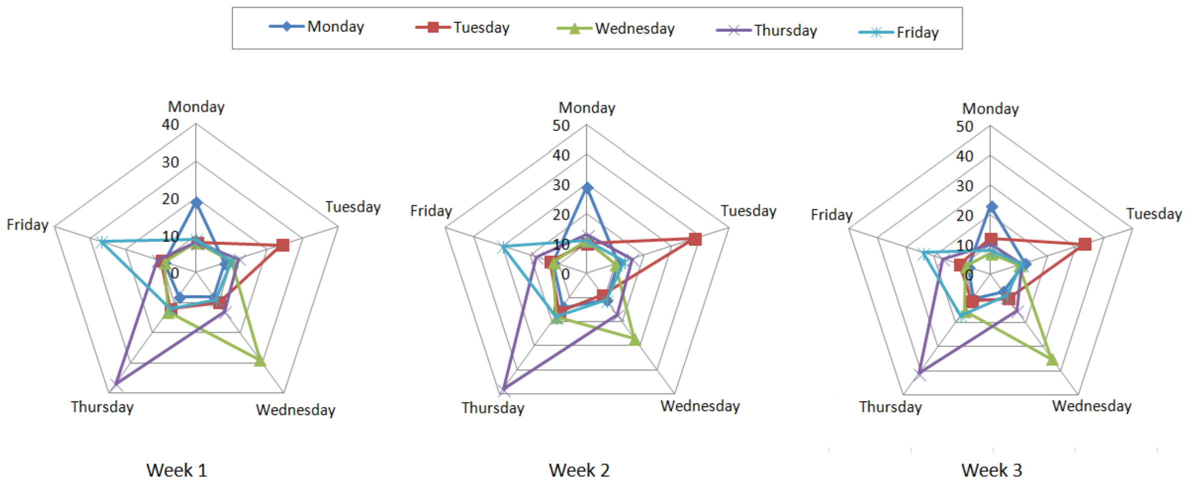


Figure 17. Distribution of common Wi-Fi address between weekdays

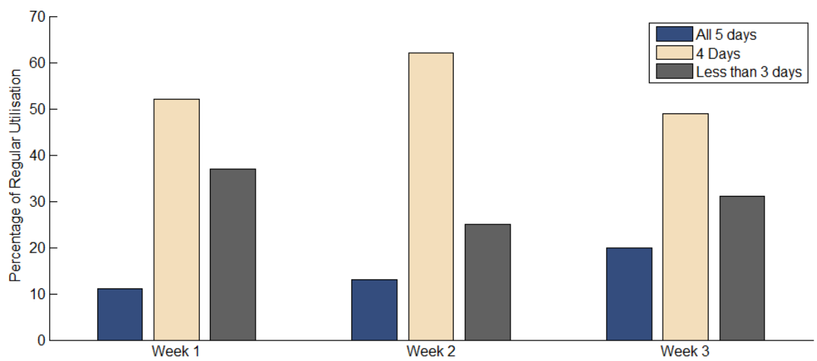


Figure 18. Distribution of the staff attendance of the area along each week

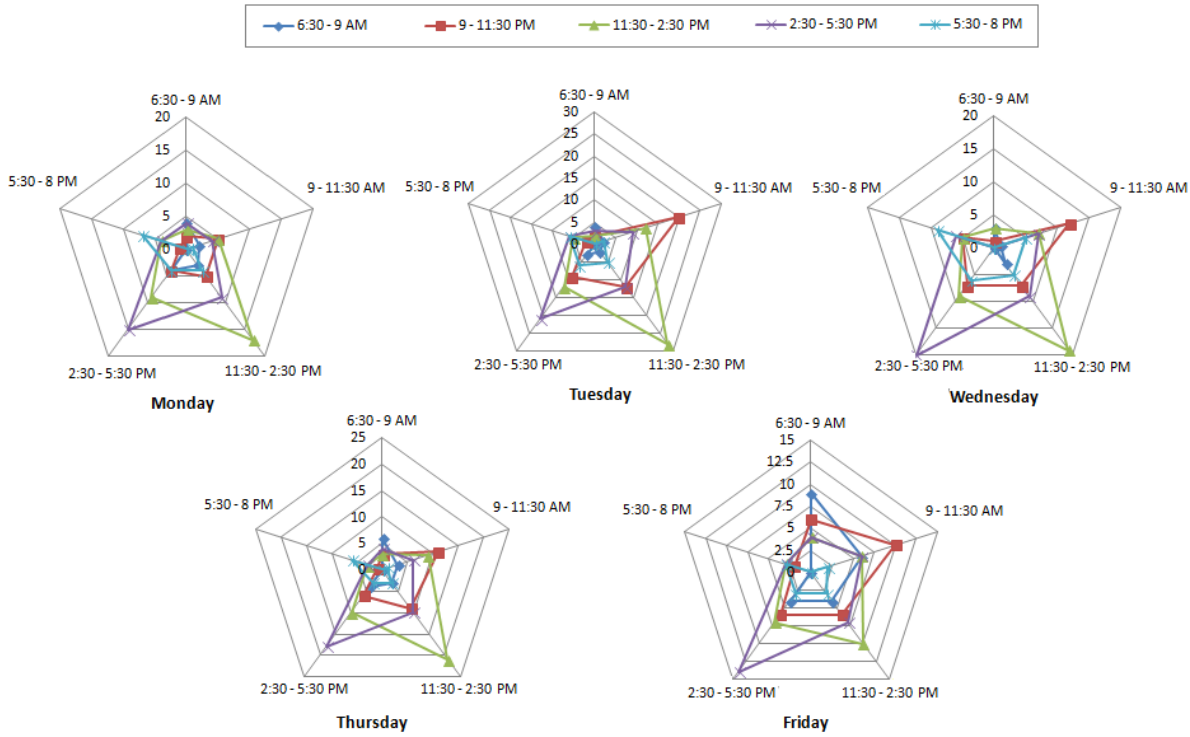


Figure 19. Distribution of common Wi-Fi address between different periods of day

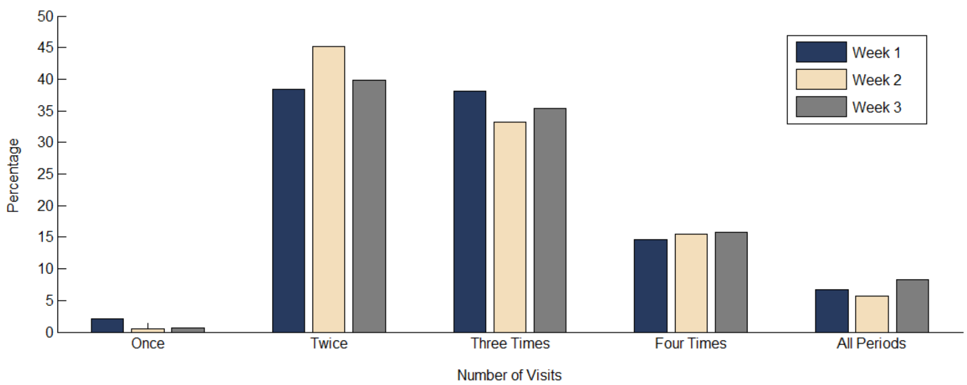


Figure 20. Frequency of utilisation

ii. Time Spending

This section presents the time spent by people in the lounge area during different periods of a day, where a day is categorised into five periods as discussed above. Figure 22 represents Box plots of the time spent (utilisation of the lounge) during week days for different time periods. Each sub plot is for different day of the week. Here, for each visit of the person, only the time spend more than 3 minutes is considered. To count valid log records, the only unique devices were considered that have being continuously observed during each day periods for at least 3 minutes. For example, if a device was observed once around 9:30 AM and once in 10:30 AM, this device was not extracted as time spending feature for *Morning* period. Figure 21 shows an example of which type of records was counted for time spending analysis. In this example, ID#2 was on observed in two periods during morning time. Both periods are less than 3 minutes and were not counted as a valid time spending data. Time periods spent by ID#1 and ID#5 are counted as valid data. The first period of ID#4 is invalid and the second period is accepted for analysis. In case of ID#3, just the time period after 9:30 AM is considered as morning time spent data.

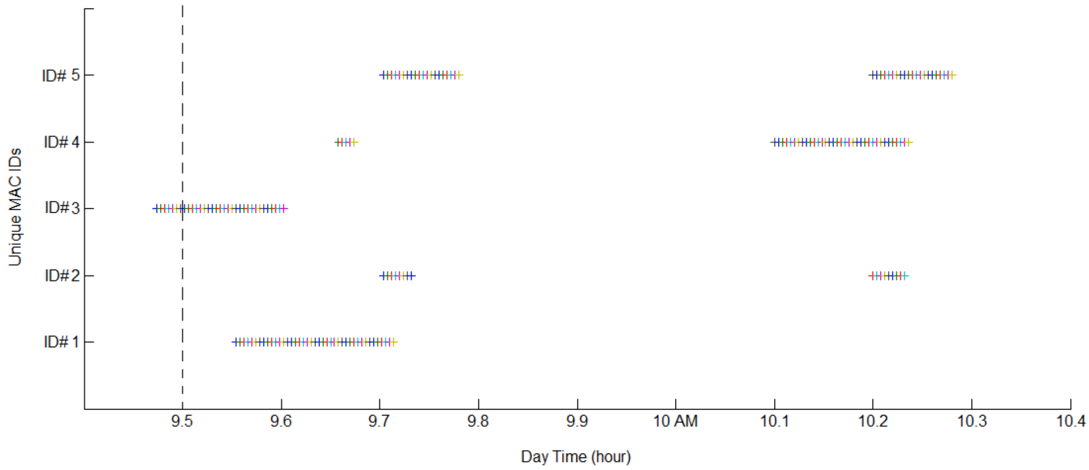


Figure 21. Example of valid and invalid records for time spending analysis

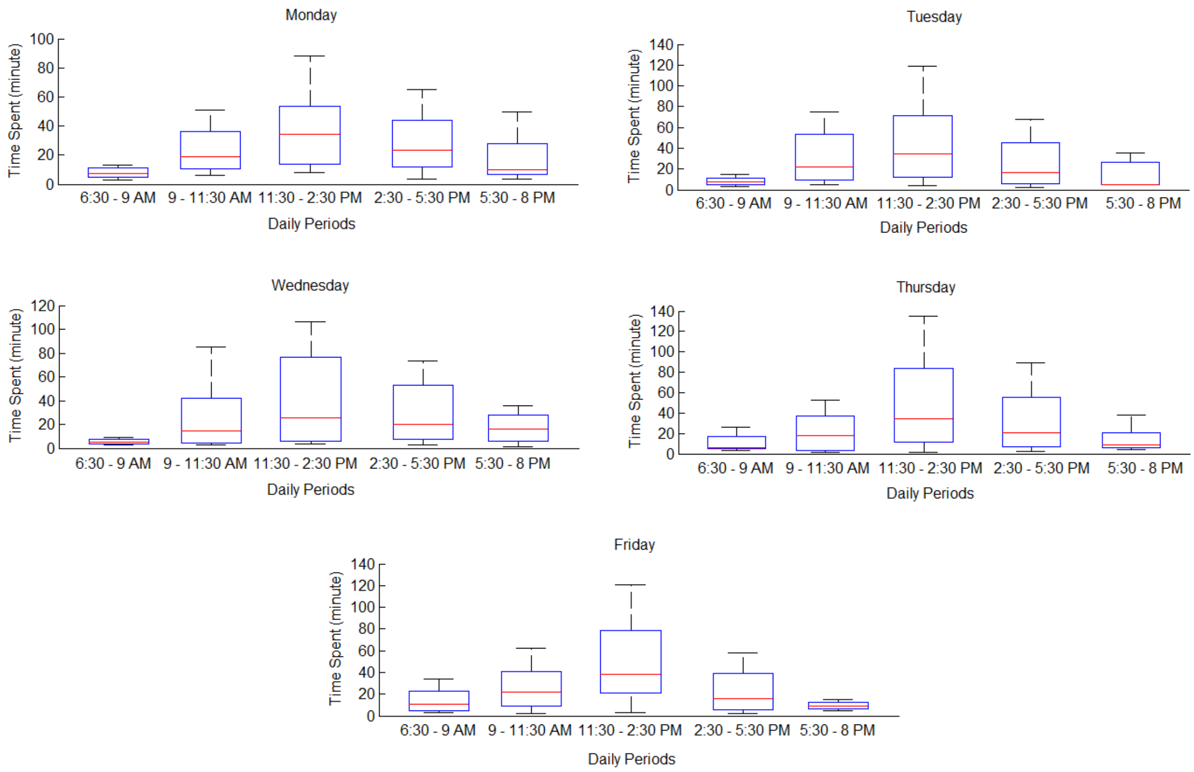


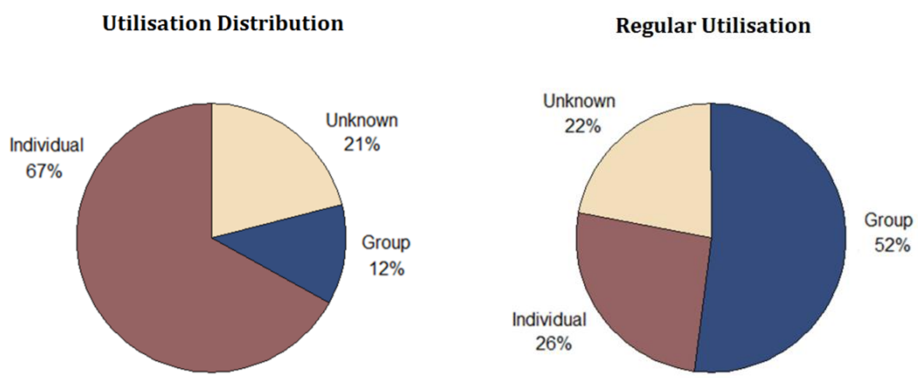
Figure 22. Frequency of utilisation

It can be concluded from Figure 22 that people spend more time during lunch periods of working day. Early morning and evening have lower amount of utilisation time. Mornings and afternoons were second popular period for staff to utilise the lounge area. In overall, the pattern of utilisation time between weekdays was almost same. These results explain that people utilise the lounge space mostly for their lunch.

iii. Group Gathering

During our analysis on the data of three consecutive weeks, some groups were found that spend their time together regularly. Here, devices which regularly entered and exited the lounge area in almost similar time (within 3 minutes) during lunch periods for all the observations were considered as a *group*. Devices which are do not enter or exit the lounge with other device in almost similar time (within 3 minutes) are considered as *individual*. The devices which are neither *individual* nor *group* are considered as *unknown*. For instance, say devices A, B and C have entered and exited the lounge for all the days expect one. On the exceptional day A and B have entered and exited together, then A and B are *grouped* where as C is *unknown*. Figure 23*a* illustrates pie charts for proportion of the devices that utilise the lounge area. It is observed that only 12% of the devices are *group* and over 67% are *individual*.

Figure 23*b* illustrates pie chart for the regular attendees. Here, only the devices which are observed during the lunch for at least three times a week (more than 50% of the week) are considered as regular attendees. It is observed that the *grouped* devices have the highest proportion of the regular attendance. It is over 52% here. This indicated that although group devices are only 12% of the visitors, but they utilise the lounge more often than *individuals*. This is further backed by the analysis between the time spending during lunch period by *individual* and *group* (see Figure 24). The median of the time spend by *group* (approx 40 minutes) is higher than that of the *individual* (approx 20 minutes).



(a) (b)

Figure 23. Group and individual utilisation

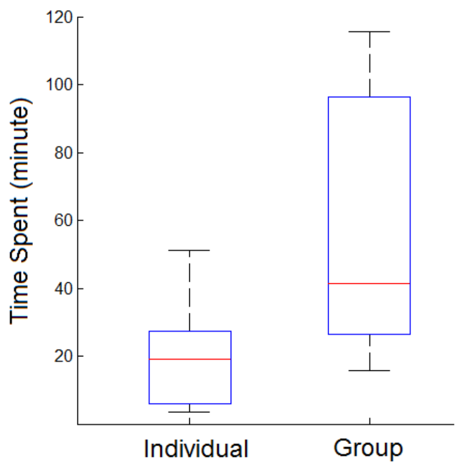


Figure 24. Group and individual time spending

4.2.5. Conclusion

The outcomes of this case study proved the functionality and significance of MAC data for human behaviour analysis. The results of this study extracted some human behaviour features that are difficult and expensive through other methods such as camera and survey. In the independent data collection mode, this tracking method could effectively extract valuable human behaviour information such as frequency of utilisation, utilisation time, group utilisation and socialising. However, the method accuracy is dependent on how many devices are turned on during the data collection.

The outcomes of this study can be applied for various purposes. By identifying the peak periods of utilisation, the facility management team can optimise their performance by selecting critical periods for inspection and providing facilities. Also, this team can be aware of people response to space design change or new facility setup such as upgraded coffee machine, adding a TV and entertainment facilities. This kind of knowledge from people behaviour can facilitate them for the implementation of future plans with minimum risks. In another aspect, the results will be useful for human resource management team to understand the social behaviour of people. This knowledge will guide them to setup plans for enhancement of their people social activities such as organising weekly or monthly social events.

The impact of environmental complexity can have a significant impact on the data range and accuracy. In this case study, some test scenarios suggested optimal equipment in terms of covering whole study area and not covering staff work stations around the study area. The test scenarios indicated that only 3 staff rooms may be covered by WiFi scanner. Accurate estimation of a Bluetooth or WiFi antenna's scanning range is a challenge in indoor spaces. This challenge is because environment's obstacles such as walls can interfere and reflect the signal depending on their materials. Some environmental obstacles may be made of composite materials. Also, we can have a general estimation of obstacle's signal interference based on Table 1. In order to have an accurate data collection, the study area must be only covered by scanner's scanning range. As making changes in indoor design requires time and can have a financial costs, adjusting the scanning range by changing scanner's antenna gain seems the better approach. Small study areas same as this case study's area require smaller antenna's gain. Test scenarios suggested to use no external antenna because the scanner range with no external antenna was only limited to the kitchen area. Any bigger antenna's gain could cover staff offices that can result is removing some valuable data. It is then suggested to set up a suitable antenna gain in order to increase data collection accuracy.

CHAPTER 5: CONCLUSION AND FUTURE DIRECTIONS

This study presented the use of MAC address data as an effective tool for tracking and analysis the spatiotemporal dynamic of human in terms of shared space utilisation behaviour. This research indeed significantly augmented the current knowledge by reporting on a recent and comprehensive experiment using MAC address data as a tracking technology. Literature review chapter covered both studies done on human movement behaviour and MAC address data as human movement tracking technology. However, limited works have been applied to track human movement in indoor spaces based on MAC address data. Also, assessment of scanning equipment was needed to be fundamentally assessed in terms of human movement monitoring.

5.1. ADDED VALUE OF MAC ADDRESS TRACKING

Assessment of scanning equipment on data collection showed that antenna gain must be selected based on environment type, size of area, and type of application in terms of human movement monitoring. Understanding scanning range helped to develop scanning strategies to localise pedestrian and cyclists during their travel. Walkers, runners and cyclists are also identified based on their travel time.

Evaluation of Bluetooth and Wi-Fi in terms of popularity of use revealed that the availability of Wi-Fi MAC addresses is highly more than Bluetooth addresses. This suggests that data collection from people based on capturing their Wi-Fi MAC address provides more efficient and confident dataset than Bluetooth data. Also, areas providing free Wi-Fi networks increase the probability of capturing more unique Wi-Fi devices.

The analysis of case study results showed that it is possible to analyse the human behaviour in different aspects based on MAC address data in terms of space utilisation. This analysis could estimate staff utilisation spent time and frequency during a day and weekdays. This approach identified and tracked the people who regularly utilise the lounge area with lower setup and processing costs. Also, this method could identify and track group gathering and presents a comparison between group and solo utilisation.

5.2. SUGGESTIONS FOR FUTURE RESEARCH

MAC address tracking technology can extract more valuable human behaviour information. This study was a successful model that investigated human behaviour in a little society. This model can be extended to larger spaces and various scenarios in order to collect data and analysis human behaviour in response to environmental and society structure. In another word, it is possible to assess spatiotemporal dynamics and behaviour of human for following goals based on MAC data:

(1) **Human socialising behaviour assessment:** The behaviour of individuals can be assessed in terms of socialising from when they relocate in a new place until they join a group for social activities. This period can be called *First Socializing Interval*. Also, the effectiveness of various social events can be evaluated in terms of decreasing *First Socializing Interval* duration.

(2) **Human social behaviour assessment:** In this case, individuals behaviour in a group society can be assessed and categorised into some divisions such as
  a. **Loyal:** people who are loyal to a group and spent most of their time with them,
  b. **Outlier:** people who leave a group and join to another group,
  c. **Flier:** people who spend their time with different groups,
  d. **Gender:** people who prefer to join to same gender groups,
  e. **Solo:** people who do not socialised.

(3) **Human response to changes of environmental structure:** Collecting MAC data during a design or structural change of a shared environment such as a workplace can demonstrate the response of people to the changes. This change can be adding or removing a facility from a workplace for example.

The outlined human information can be acquired by MAC tracking technology that other human tracking technologies are not able to extract and study these information. As a future direction for enhancement of monitoring human movement, complementing of MAC data with camera and other tools can remarkably develop human behaviour information collection part and deliver new and abstruse features of human behaviour. Tracking human's movement behaviour is also important in terms of improving crowd evacuation plans. This study showed that monitoring people's movement based on MAC address data can be useful to better understanding of human movement behaviour. This information can add a significant value to future urban and interior design as well as improving crowd evacuation strategies.

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